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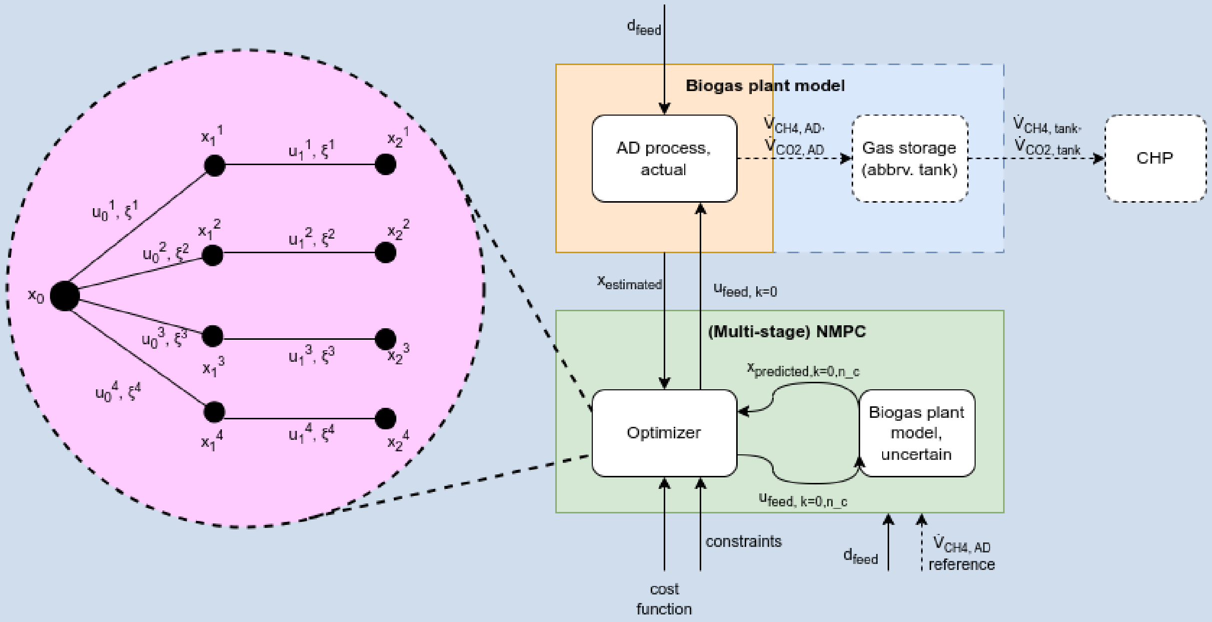

Demand-oriented Optimal Feeding of Agricultural Anaerobic Digestion Plant under Uncertain Substrate Characterization

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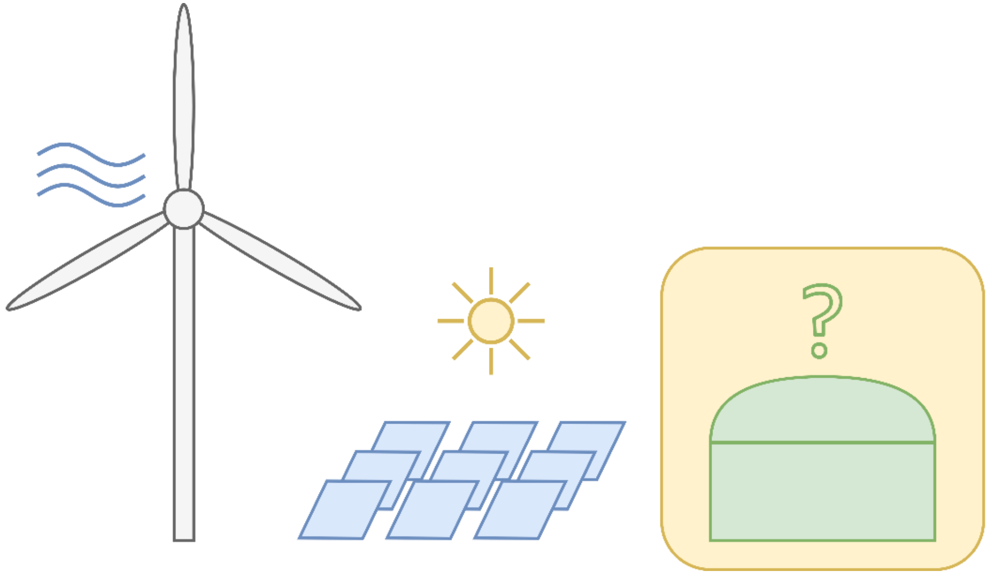
Problem
- more than 9000 biogas plants in Germany (as of 2017)
- typically subsidized through Renewable Energy Act (German: "EEG")
  ➡ guaranteed feed-in tariffs for electricity
- biogas plant operation for electricity generation significantly less profitable after EEG funding period ends

Motivation for biogas plants to stay

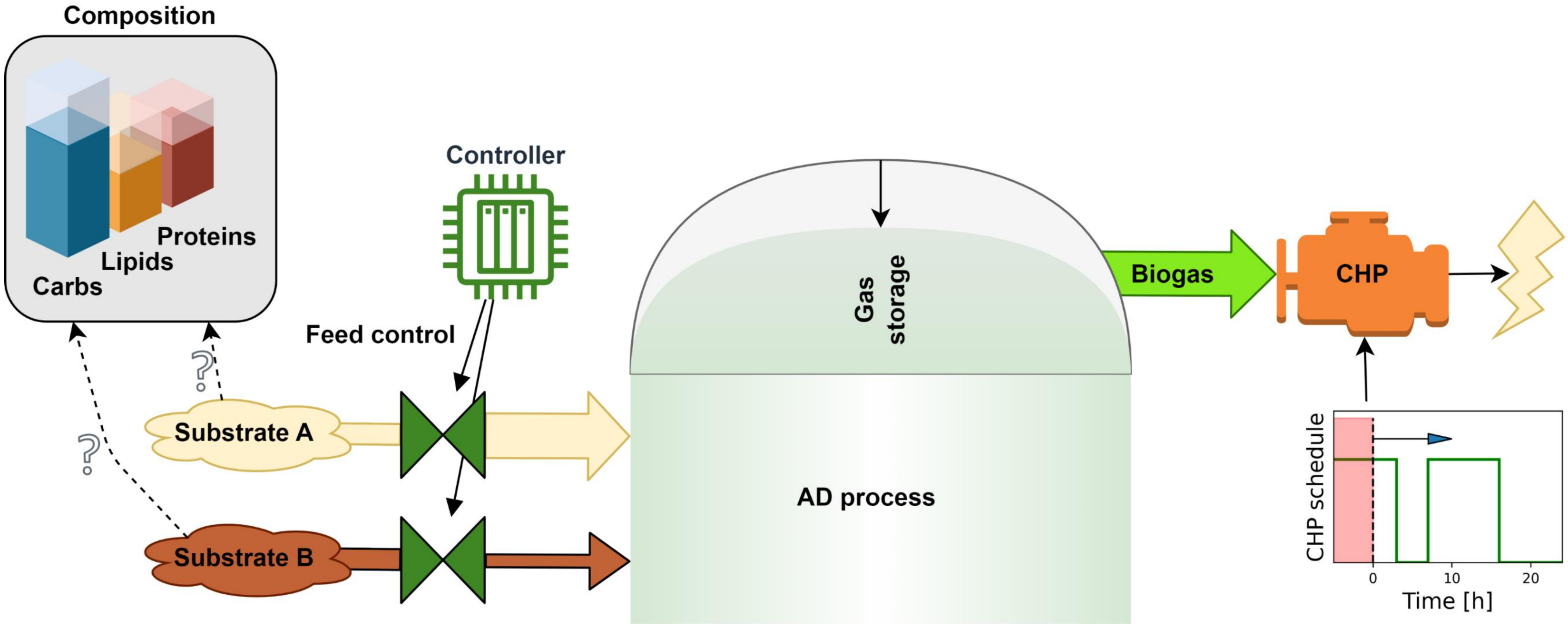
biogas production not directly dependent on environmental conditions
➡ controllable, reliable renewable energy



Profitability increase approaches
- increase revenue:
  - demand-oriented electricity production
    ➡ higher feed-in tariffs
- reduce costs:
  - substrates
  - infrastructure

Solution idea

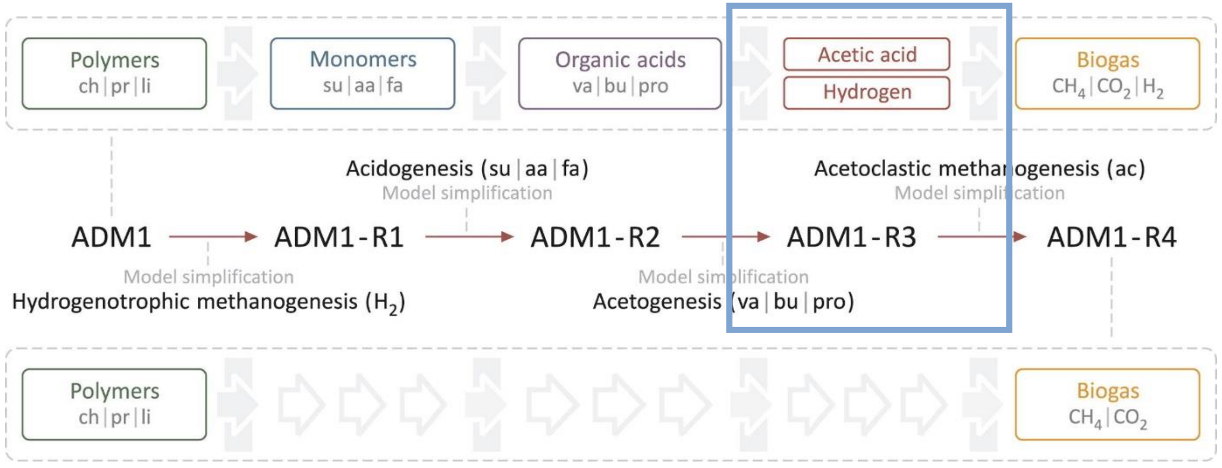
Approach
produce biogas on demand by controlling AD process through feeding of not measured waste substrates
➡ allowing for smaller gas storage



Model

AD plant
- CSTR based on simplified ADM1 model (ADM1-R3-frac) with multiple inputs
- inputs: Feed volume flows of respective substrate
- 18 states
  - soluble and particulate components in liquid phase
  - gaseous components in gas phase
  - differentiation between fast and slowly digestible carbohydrates

Gas storage
- mixture of ideal gases at isobaric conditions
- modeled using volume balance
- comprises CH_4, CO_2, H_2O gases
- 2 states for CH_4 and CO_2 volumes respectively
- H_2O volume computed dependently



[Weinrich 2021]

$$\dot{V}_{CH_4,tank} = \boxed{\dot{V}_{CH_4,in}} - \boxed{\dot{V}_{CH_4,out}}$$
$$\dot{V}_{CO_2,tank} = \boxed{\dot{V}_{CO_2,in}} - \boxed{\dot{V}_{CO_2,out}}$$

From AD model   Defined by CHP power demand

Substrate composition

Problem

- AD model requires inlet concentrations ξ_i of macronutrients
- can be computed from other properties
  - Example: $\xi_{ch} = \overline{FQ}_{\mathrm{ch}} \cdot \overline{X}_{\mathrm{ch}} \cdot DM \cdot \rho_{\mathrm{FM}}$

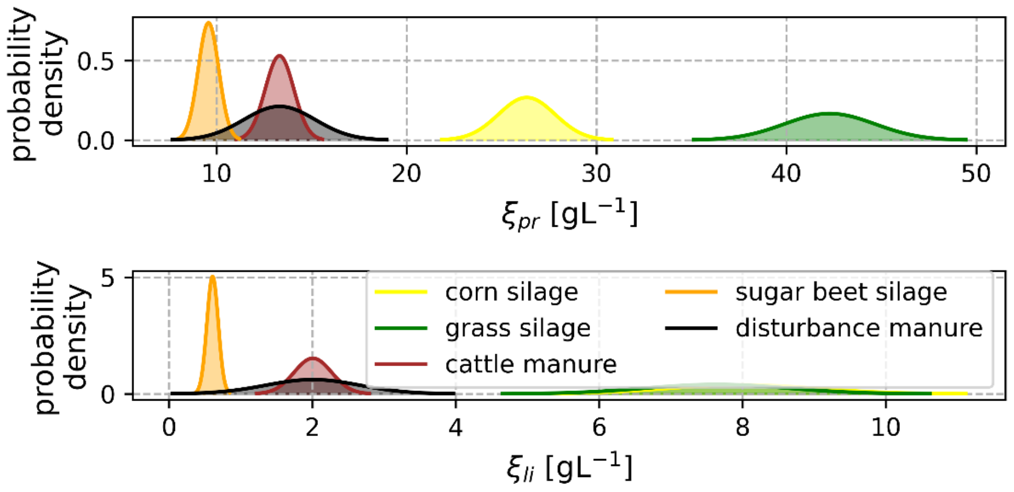
with
ξ_{ch}	inlet concentration of carbohydrates
$\overline{FQ}_{ch}$	fermentable fraction of carbohydrates
$\overline{X}_{ch}$	raw concentration of carbohydrates
DM	dry matter fraction
ρ_{FM}	density of fresh matter

- fermentable fraction of macronutrients cannot be measured directly

Approach

- proteins and lipids assumed to be fully fermentable
- carbohydrate fermentability adjusted to meet total fermentation quotient of substrate
- data taken from literature and not yet published ring trials
- uncertainties of ξ_i linearly propagated

computed probability densities of inlet concentrations



➡ Substrate macronutrient composition uncertainty quantified

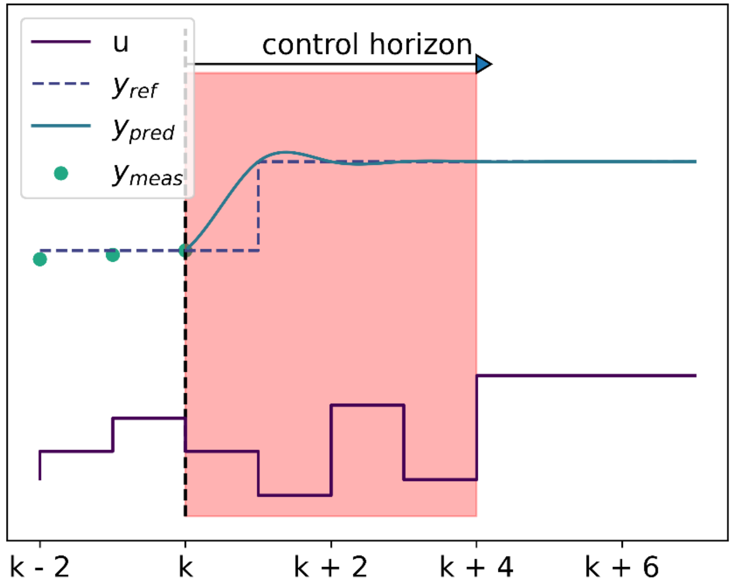
Model Predictive Control

- optimization based control scheme
- desired system behavior (e.g. setpoint tracking) described in cost function
- prerequisite: Model description for system

Algorithm idea

1. computation of optimal input trajectory across control horizon
2. application of first computed input
3. measure system states

repeat



Pros

- Easy implementation of process constraints
- Multi-variable control
- Incorporation of economic incentives in cost function

Multi-stage NMPC

Problem

- true substrate composition unknown ➡ parametric uncertainty
- robust control strategy required to guarantee constraint satisfaction

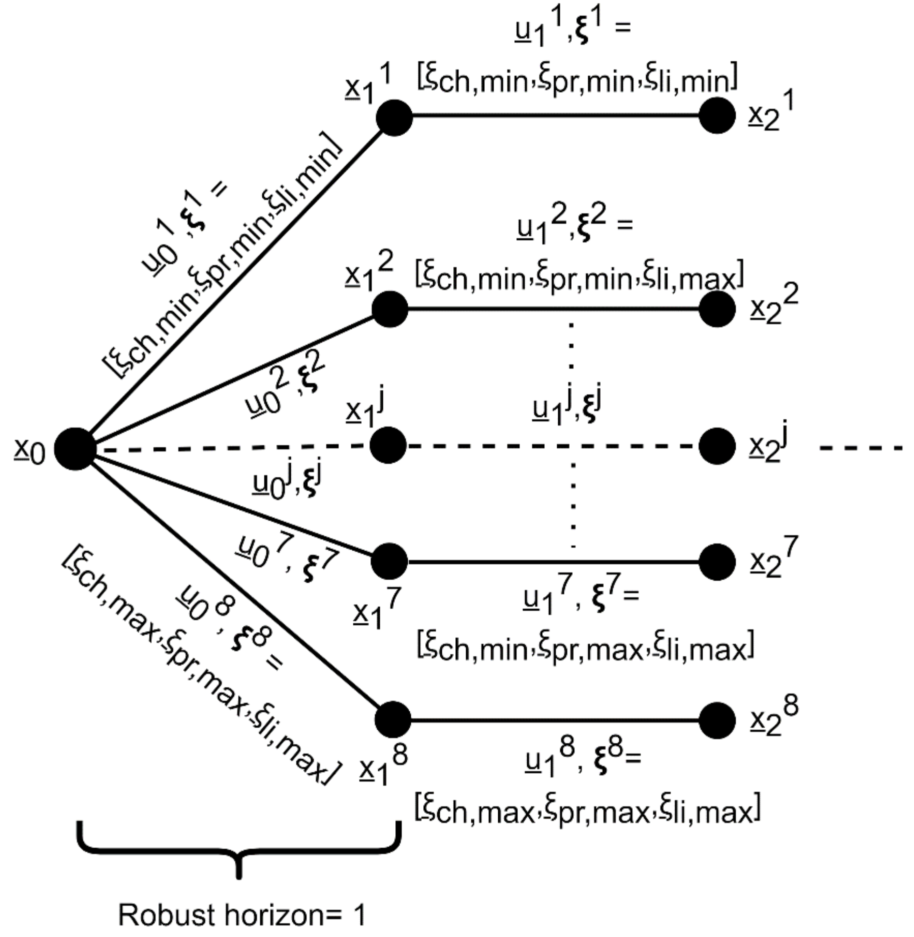
Assumption

uncertain parameters only have discrete realization values

Multi-stage NMPC – Methodology *[Lucia 2013]*

- combine all discrete uncertainty realizations
- each combination of realizations represents scenario
- optimize control action over entire tree ➡ weighted summation of scenario specific cost functions

Scenario tree of multi-stage NMPC with substrate uncertainties



➡ control scheme tailored to problems with parametric uncertainties

Simulation scenarios

General
- preceding steady state initialization (300 days)
- 30 day optimal feeding
- 4 input substrates: 3 silages, 1 manure

Noise/errors
- uniform random noise in gas storage filling states
- random uniform feeding errors of $\pm 5\%$

Disturbance
- forced feeding of cattle manure
- 2.5 times larger composition uncertainty

Substrate composition

variation of $\pm 1.5\sigma$ w.r.t. nominal value

➡ parametric plant-model mismatch

Parameter	Value
CHP electrical capacity	50 kW
Digester liquid volume	163 m^3
Gas storage volume	296 m^3
Average week day CHP operation	13.8 h/d
Average weekend CHP operation	9 h/d
Time step	0.5 h

Scenarios
- methanation scenario
  - ➡ set-point tracking of methane volume outflow
- demand-oriented scenario
  - ➡ fulfillment of typical CHP schedule

➡ application of controllers in two different simulation scenarios

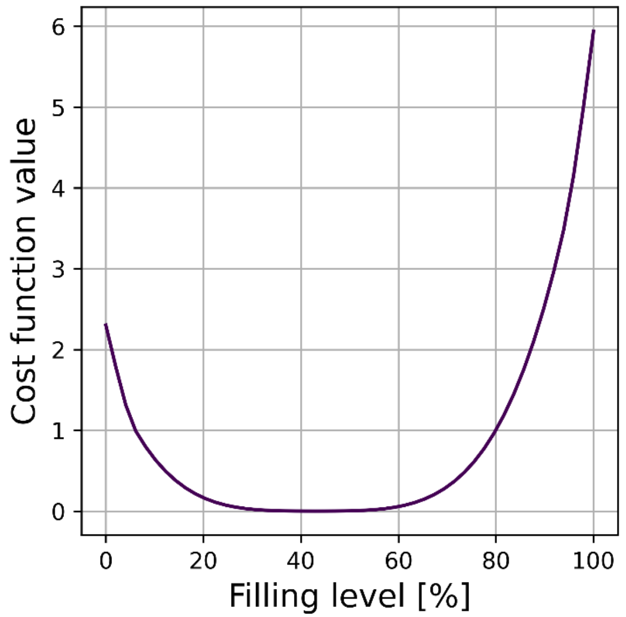
Optimization setup

Scenario specific cost function (demand-oriented scenario)

$$\min_{\underline{u}_{0:N_c-1},\underline{x}_{0:N_c}} \quad J_l(\underline{x}_k,\underline{u}_k) = \sum_{k=0}^{N_c-1}\Bigg(c_1 \cdot \Big(\text{Deviation from filling level setpoint}\Big)^2 + c_2 \cdot \Big(\text{Deviation from filling level setpoint}\Big)^4\Bigg) + \sum_{k=0}^{N_c-1}\sum_{i=1}^{M}\frac{cost_i}{cost_{max}}\cdot u_{i,k}$$

subject to
$$\underline{x}_{k+1} = \mathbf{F}(\underline{x}_k,\underline{u}_k)$$
$$\underline{y}_k = \mathbf{H}(\underline{x}_k)$$
$$u_{i,k} \in [0,1] \quad \forall \quad i \in \{1,\dots,4\}, k \in \{0,..,N_c\}$$
Hard and soft constraints for gas fill

Cost function with respect to filling level (demand-oriented scenario)



Cost function components

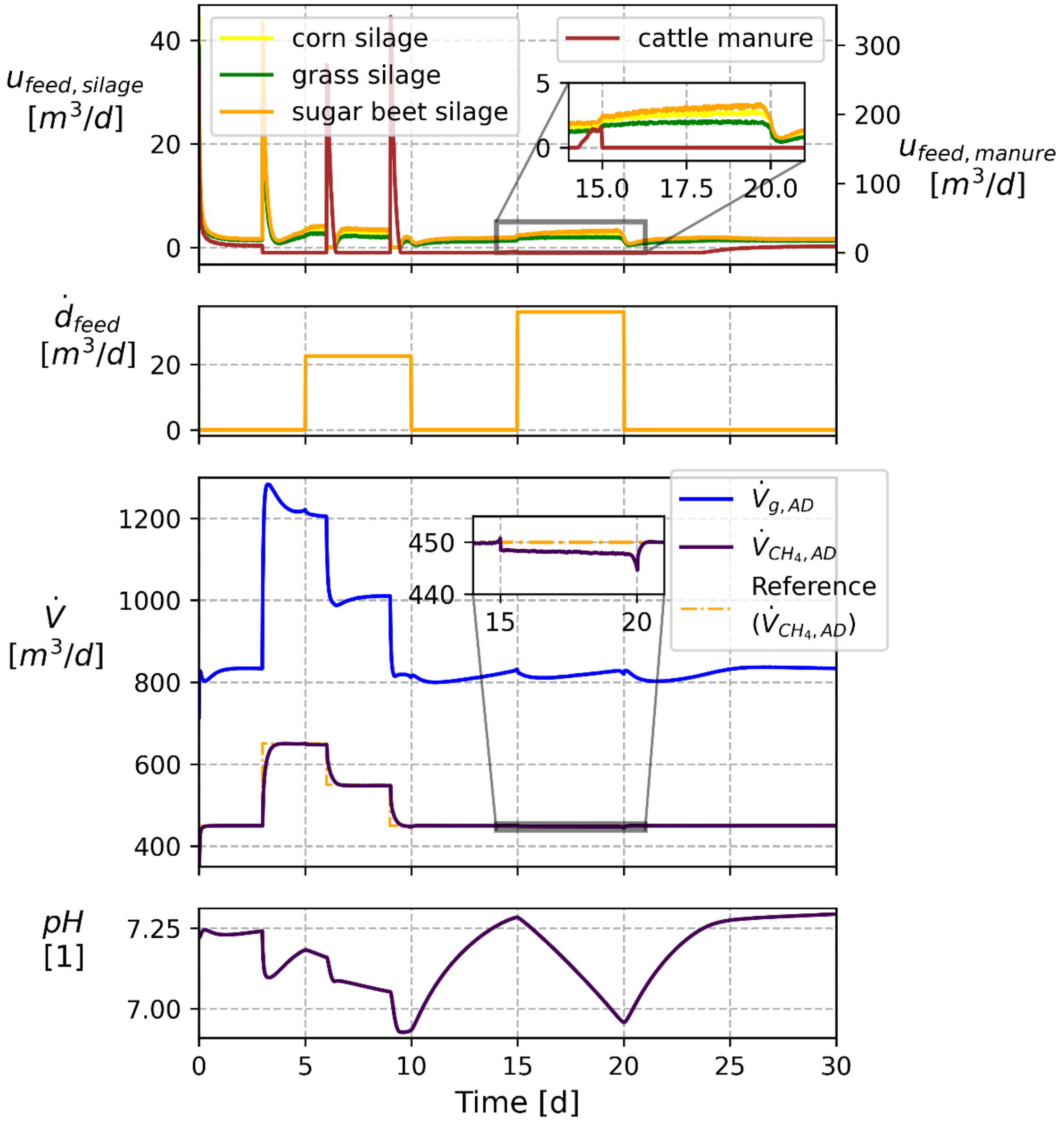
- deviation of filling level from setpoint at 43%
  - below 50% ➡ production increase easier than decrease
  - filling level comprised of three normalized gases
- substrate usage weighted by respective substrate cost

Constraints

- hard and soft constraints of filling level representing physical limits
- individual hard constraints for CO_2 and CH_4 to prevent negative individual volumes

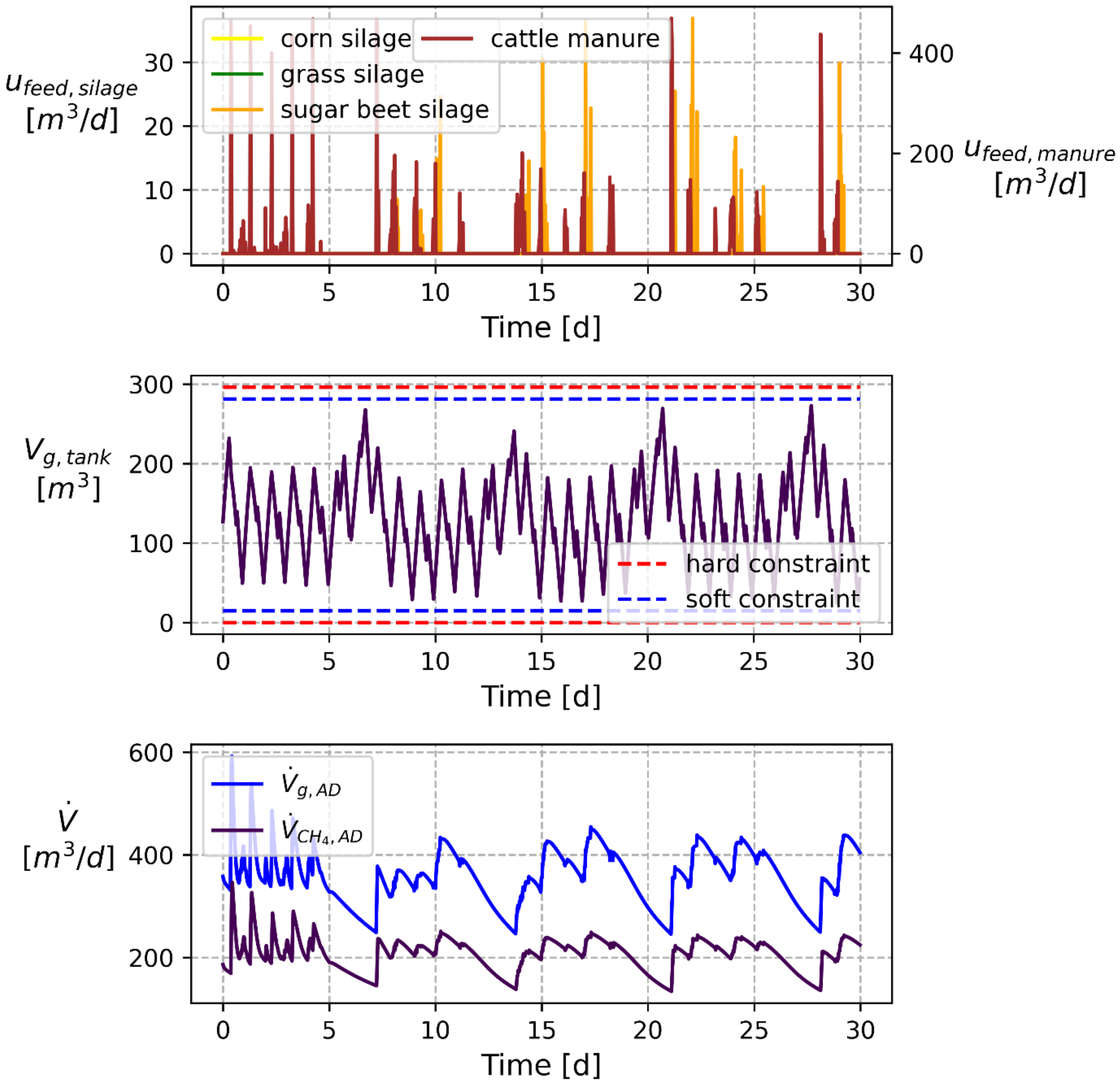
➡ cost function for demand-oriented scenario incorporates filling level and substrate costs

Results - Methanation Scenario



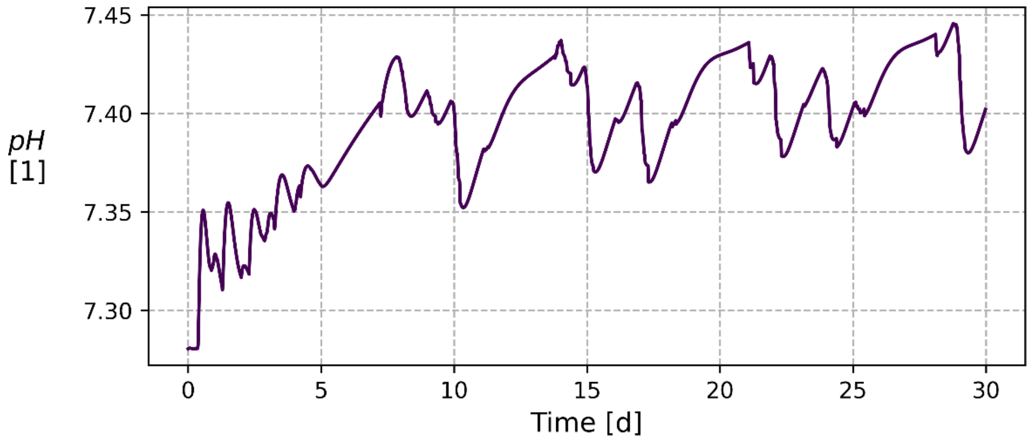
Findings

- generally very good reference tracking
- setpoint changes addressed by large feeding inputs
  ➡ but: accompanied by significant pH drops
- silages fed to increase biogas production
  - larger macronutrient density as compared to manure ➡ quickly digestible
- manure fed to brake biogas production
  - due to low density of macronutrients and in absence of buffer solution
- pH drops due to large disturbance feeding could not be compensated



Findings

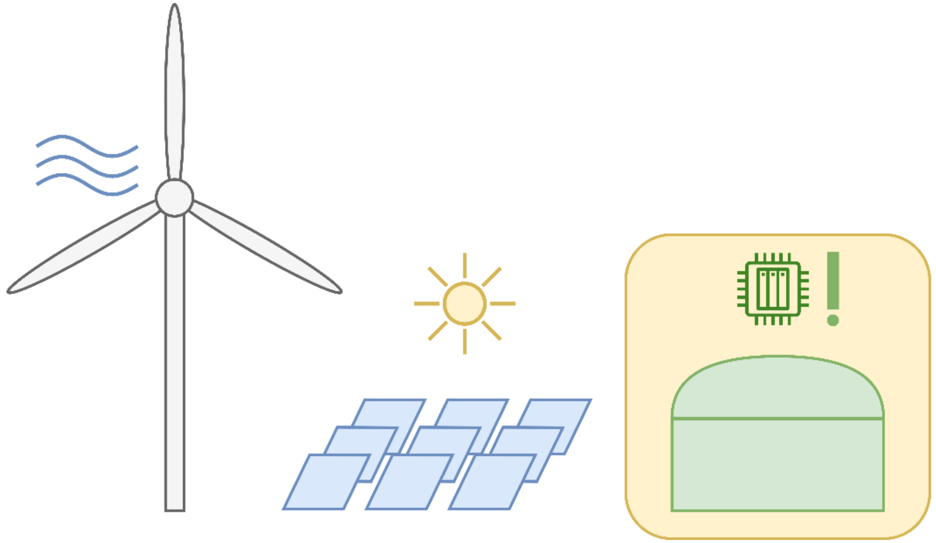
- constraints were not violated
- shorter CHP operating times (e.g. on weekends) could only be handled for a certain time
- gas storage size larger than in comparable study with simpler model *[Mauky 2016]* but smaller than in other studies
- process stability maintained ➡ see pH plot
- significant changes in biogas production realized dependent on CHP demand schedule



Summary and Outlook

Summary

- explored a potentially more profitable pathway for biogas plant operation: demand-oriented feed control with substrates of uncertain composition
- developed multi-stage and nominal NMPC controllers
- tested on two different simulation scenarios
- developed a software framework
    - extensible with observers, etc.
    - real-time application computationally feasible



Limitations

- simulations only
- full state information assumed
- power demand assumed to be known

Outlook

- comparison between multi-stage NMPC and nominal NMPC for demand-oriented scenario
- observer implementation for non-measurable state variables
- economic assessment of proposed control scheme
- hierarchical control design with top level optimizing for optimal filling level

References

[Lucia 2013] Lucia, S.; Finkler, T.; Engell, S. 2013. Multi-stage nonlinear model predictive control applied to a semi-batch polymerization reactor under uncertainty. Journal of Process Control 23: 1306–1319.

[Mauky 2016] Mauky, E.; Weinrich, S.; Nägele, H.-J.; Jacobi, H.F.; Liebetrau, J.; Nelles, M. 2016. Model Predictive Control for Demand-Driven Biogas Production in Full Scale. Chemical Engineering & Technology 39: 652–664.

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